Knowledge Base of Industrial Cluster and Start-ups' Innovation Performance

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ABSTRACT

This study explores the impact of knowledge stock and knowledge centrality, which are the two main characteristics of innovative start-ups' entry technologies in the local knowledge base, on firms' technological innovation and diversification. It tests the hypotheses with patent and firm-level data of innovative start-ups in Shanghai Information Communication Technology cluster from 1985 to 2009. The results show that knowledge stock and centrality has positive influence on firms' technological innovations in their entry fields. Individually, knowledge stock and centrality has negative impact on start-ups' technological diversification. However, there is a significant complementary effect on start-ups' technological diversification between these two factors.

Keywords:

Innovative start-up firm; knowledge base of industrial cluster; technological innovation and diversification

INTRODUCTION

Geographic location has been recognized as one of the key factors in explaining firm's performance, because a firm could benefit from multiple types of agglomeration externalities (Arrow, 1962; Jacobs, 1969; Marshall, 1920; Romer, 1986). Among various sources generating agglomeration externalities such as specialized suppliers, inputs at lower costs and skilled labor market from supply side and the sophisticated customer and heightened demand from demand side, localized knowledge spillover is regarded as a key ingredient of innovation and technological change (Audretsch and Feldman, 1996 and 2003; Jaffe, Trajtenberg and Henderson, 1993; Kesidou, Caniëls and Romijn, 2009). While identifying the importance of geographic agglomeration and knowledge spillover, the literature provides little insight as to how and why knowledge spills over (Audretsch and Feldman, 2003). Therefore, the way in which knowledge is most likely to spill over and the performance implication remain unclear. There are several questions still left unanswered: Why do firms within a cluster have different levels of technological innovation? Why do some firms become technologically specialized and others become diversified over time in their innovation activities within the same geographic location? How do localized knowledge spillovers influence a firm's innovation performance?

Drawing on the economic geography and innovation strategy literature, I investigate the impact of knowledge stock and knowledge centrality of innovative start-ups' entry technologies in the local knowledge base on firms' technological innovation and diversification through distinguishing the different types of technological knowledge that are agglomerated in a cluster and examining the way in which these knowledge are agglomerated (e.g. relatedness of different types of technological knowledge in the local knowledge base). ***Industry cluster*** is defined as a geographic concentration of firms operating in the same or related industries (Krugman, 1991;

Porter, 1998). ***Knowledge base*** of an industrial cluster is characterized by two sets of attributes (Ramani and Looze, 2002): one attribute is ***knowledge stock*** which reflects the quantity or strength of the technological knowledge in a cluster and the other one is ***knowledge centrality*** which indicates the relatedness the focal technological knowledge with other knowledge fields. ***Innovative start-up's entry technology*** is the technology field that an innovative start-up firm chooses to start with and to build upon its business in an industrial cluster. I develop arguments which contend that knowledge stock of an innovative start-up's entry technology in the local knowledge base has a positive effect on the firm's technological innovation but negatively influences the firm's technological diversification. Knowledge centrality positively associated with both firm's technological innovation and technological diversification. These two factors have complementary effect on the firm's technological diversification.

The sample is ***innovative start-ups*** which are newly founded firms applying their first patents shortly after their foundation in Shanghai ICT cluster from 1985 to2009. Based on China patent data and firm-level data, I test the proposed hypotheses with different specifications of negative binomial and probit model. I find that innovative start-ups have more technological innovations in the entry fields if their entry technologies are characterized by higher levels of knowledge stock or knowledge centrality in the local knowledge base. Over time these firms demonstrate different propensities for technological diversification in their innovation activities. Knowledge stock and centrality shows negative effect on the probability of firm's technological diversification. The interaction between knowledge stock and centrality shows positive effects. Innovative start-ups are more likely to diversify into other technological fields when both the knowledge stock and centrality retains a higher level.

This study offers two main contributions to the economic geography and innovation strategy literature. First, Start-up firms are known to be more prevalent in regions where industry clustering exists (Stuart and Sorenson, 2003) due to the lower costs associated with learning about the business environment for the industries of the region (Maskell, 2001). At the same time, start-up firms experience strikingly high failure rate. The way in which clusters affect start-ups' performance becomes a interesting question, yet receives limited attention. There is a large body of literature on the determinants of variation in new firm formation (e.g. Fritsch 1992; Keeble and Walker 1994; Sutaria and Hicks 2004) but very little evidence supporting that the factors fostering start-ups are the same as those, which are important for their future success (Brixy and Grotz, 2007). This study will focus on the relationship between the knowledge base of a cluster and the performance of innovative start-up and help us understand the way in which knowledge spills over among the firms within a cluster and facilitate innovative start-ups in evaluating and responding to the potential technological opportunities. Second, unlike existing studies which mainly adopt aggregated measures of the resources agglomerated in a cluster such as the location dummy which indicates whether or not a firms is located in a cluster and the size of a cluster which captures the number of firms (or innovations) in the same or related industries, I explore the local knowledge base in a way that provides information on the specificity of each type of technological knowledge (e.g. the composition and relatedness of the knowledge in a cluster) which could influence the route and potential of knowledge spillover due to the differential strength and the connections of a particular knowledge type with others. Based on the patent data, analysis carried out at the technology level provides us a deeper understanding on the mechanism of local knowledge spillover at a micro and fundamental level.

The rest of the study is structured as follows. I briefly review the background literature. Thereafter, I develop theoretical arguments leading to the hypotheses, explain the research methodology, present the results and close the study with a discussion of the findings, limitations and avenues for the future research.

THEORY AND HYPOTHESES

Cluster, Knowledge Spillover and Firm's Innovation Activity

There has been a long and insightful literature that considers the spatial dimension of innovative activity and the factors that influence technology change. Baptista and Swann (1998) have observed firms located in strong industrial clusters or regions are more likely to innovate than firms outside these regions and attributed the existence and success of clusters to the pervasiveness of knowledge externalities or spillovers. Jaffe et al. (1993) and Frost (2001) point out that a firm's innovation activities are influenced by the innovation activities of nearby firms, which provides strong evidence for the presence of knowledge spillovers. Beaudry and Breschi (2003) explore empirically whether firms located in strong industrial clusters are more innovative than firms located outside these regions and show that a firm is more likely to innovate if located in a region where there is strong presence of innovative firms and a large pool of potential spillovers associated with a large accumulated stock of knowledge. The theoretical foundation of these studies is mainly based on the *agglomeration/localization economies* (Marshall, 1920) which come from the clustering of firms in the same industry or the *urbanization economies* (Jacobs, 1969) that are generated from the local diversity of economic activities outside the focal industry. The problem with this stream of literature is that the driving forces behind these regional advantages are not clear. There are several sources of externalities from both the supply-side (e.g. specialized suppliers, inputs at lower costs, skilled labor market and knowledge spillover) and the demand-side (e.g. sophisticated customer and heightened demand), however, various advantages of agglomeration are usually examined as an undifferentiated phenomenon (Kesidou and Szirmai, 2008). Some scholars (e.g. Frost, 2001; Jaffe et. al., 1993) have provided evidence for the presence of localized knowledge spillovers, but they do not examine the impact on firm's innovation specifically.

Knowledge spillover refers to the effect of research performed in one economic unit in improving technology in other economic units without the latter having to pay for it (Griliches, 1992). It has received increasing attention as a key ingredient of innovation among various sources generating agglomeration externality (Audresch and Feldman, 1996, 2003; Jaffe et al., 1993). Knowledge spillovers are typically generated by firms engaging in innovation activities and are valued as they provide knowledge that is new to the receiving firms (Gilbert, et. al., 2008). Knowledge spillovers tend to be geographically localized (Jaffe et al., 1993). Geographic location thus provides a platform upon which new economic knowledge can be produced, harnessed and commercialized into innovations (Audretsch and Feldman, 2003). Firms located in clusters have better access to information than do other firms (Bianchi and Bellini, 1991; Porter, 1990; Pouder and St. John, 1996) due to the common knowledge forming a cluster level of absorptive capacity and directly observing their rivals. With knowledge spillovers, firms are equipped with industry specific knowledge. Such knowledge of other firms' innovation activities will reduce the costs associated with the search for new knowledge and stimulate the creation of innovation (Duranton and Puga, 2001; Helsley and Strange, 2002).

Existing studies examine 'agglomeration' mainly from two aspects: one is the geographic scope of agglomeration which is reflected by distance-based measures such as the geographic distance (e.g. Rosenthal and Strange, 2003), zip codes (e.g. Chung & Kalnins, 2001), metropolitan statistical areas (e.g. Shaver and Flyer, 2000). The other aspect is the magnitude or strength of agglomeration which is captured by size-based measures such as the number of firms, plants, total number of employment and patents of a particular industry (e.g. Beaudry and Swann 2001; Gilbert et. al., 2008) or other related industries (e.g. Ciccone 2002; Beaudry and Breschi, 2003; Henderson 2003), revealing the 'intra-industry' and the 'inter-industry' effects respectively. The basic premise of these studies is that the agglomeration externalities increase with the size or strength of the cluster. One limit of the above mentioned studies is that they do not fully reflect the nature and specificities of the agglomerated knowledge and do not provide information on such questions as which types of knowledge are more likely to spill over and in which way they spill over. Understanding these questions is important because knowledge spillover is not only determined by the overall strength of knowledge resources but also depends on the knowledge compositions and the relatedness among them (Porter, 1998; St. John and Pouder, 2006).

Knowledge Stock and Knowledge Centrality

There is an increasing awareness that it is not so much the regional specialization or diversification per se that induces knowledge spillovers, innovation activities and regional growth (Bae and Koo, 2008; Boschma and Frenken, 2009) but the nature of the local knowledge such as the strength of each component of the knowledge base at the disaggregate level and the relatedness among different types of knowledge in a cluster are also considered very important. Within an industrial cluster, various kinds of knowledge that belong to different technology fields with distinctive natures are pooled together and these differences influence the relevance and the level of spillover of each type of technological knowledge.

Knowledge base is defined by Ramani and Looze (2002) as a collection of the technological knowledge that an agent (i.e. an individual, institution, a region or a nation) possesses and the connections among these knowledge. Building upon their study, I characterize the knowledge base of a geographic location by two attributes: one is ***knowledge stock*** which reflects the quantity of a certain type of technological knowledge within an industrial cluster. The other attribute is ***knowledge centrality*** which indicates the relatedness the focal technological knowledge with other types of knowledge field. I use this idea as an initial building block to capture the effect of knowledge spillover from both the strength of the components (i.e. the amount of each type of technological knowledge) and their relations (i.e. the relatedness among different types of technological knowledge) in the local knowledge base.

Entry Technology and Absorptive Capacity

Firms do not benefit equally from the knowledge spillovers. Geographic proximity facilitates firms to access external knowledge spillovers, but it does not necessarily guarantee that the innovative start-ups absorb the knowledge spillovers and transfer them into a competitive advantage. Firms assimilate knowledge better when this knowledge is related to their technological capabilities (Audretsch and Lehmann, 2006). An important insight introduced by Cohen and Levinthal (1990) is that firms need to invest in the capacity to access and absorb external knowledge and the investment in R&D can work as a mechanism facilitating the absorption of external knowledge. The concepts of localized knowledge spillover and absorptive capacity – the ability of economic agents to recognize, assimilate and apply new scientific knowledge are thus closely linked (Agrawal, 2000).

A firm's entry technology refers to the technological field in which a start-up firm chooses to build its business at the time of foundation. The choice of entry technology is one of the most important decisions included in the start-up's technology strategy which guides a firm's decisions on the development of technological capabilities and the corresponding investment (Zahra, 1996). Firm's entry technology is captured in this study by the technological field of the first patent applied for by a start-up firm shortly after its foundation. It reflects the capabilities a firm possesses to develop a certain type of technology. This is because patenting activity is technologically challenging and financially demanding. A start-up firm applying for a patent in a certain technology field soon after its foundation indicates that this firm has devoted sufficient effort and resources and gained a certain amount of capabilities in the frontier of this technology field. These initial resources and capabilities of start-ups determine their ability to access and benefit from the full potential of cluster externalities (Pe'er, Vertinsky and King, 2006). So I claim that innovative start-up firm's entry technology represents a very important technological capability that is specific for the firms. It can be served as 'absorptive capacity' and make the firm more capable to recognize, assimilate and apply some particular kinds of knowledge that spills over from other organizations. Innovative start-ups with different entry technologies thus experience, process and response to the new knowledge from their environment differently.

Characteristics of Local Knowledge Base and Technological Innovation

The level of knowledge spillovers in a geographic region is influenced by the quantity of the knowledge created in this region (Acs, Braunerhjelm, Audretsch and Carlsson, 2009; Audretsch and Lehman, 2005; Beaudry and Breschi, 2003). Higher level of external knowledge indicates greater technological opportunity and higher probability of knowledge spillover (Cohen and Levinthal, 1990). In this paper, I conduct analysis at the technology level, distinguish the types of the technological knowledge and examine the strength of each knowledge type in the cluster in order to capture precisely the different levels of spillover of various knowledge and how these differences influence firms' innovation performance. An innovative start-up firm that enters with technology characterized by a higher knowledge stock will experience more intense knowledge spillover from the entry field than might be true for innovative firms that enter with technologies characterized by lower levels of knowledge stock. This is because, firstly, the firm exposes to a larger pool of discoveries and ideas (Audretsch and Feldman, 1996; 1999) and secondly, the firm is more capable to recognize the values and assimilate this particular kind of knowledge from external environment (Cohen and Levinthal, 1990). This process will in turn facilitate the firm introduce more innovations. So I propose that:

Hypothesis 1 (H1): An innovative start-up firm will produce more technological innovations if its entry technology is characterized by a higher level of knowledge stock in the local knowledge base.

Firms do not only expose to the knowledge spillovers from their own technological field but also receive knowledge spillovers from other technological domains because the same type of technological knowledge can be applied to several other fields. This relatedness between the technologies used by firms in a cluster is thought to affect the nature and scope of knowledge spillovers (Boschma and Frenken, 2009) as they share a certain degree of heuristics and scientific principles (Breschi, Lissoni and Malerba, 2003) and knowledge is more likely to spill over between the fields when their cognitive distance is not too large to ensure effective communication and interactive learning (Nooteboom, 2000).

Based on the above argument, we could understand that the creation of new knowledge in one field depends not only on the magnitude of the investment in knowledge creation in that field per se, but also depends on knowledge spillovers from other related fields. These spillovers depend on the centrality of a certain technology field which capture the relatedness among the different fields through which there is a circulation and spillover of knowledge (Ramani and Looze, 2002). The more the focal technological field relates to other technological fields the more knowledge spillovers it receives whenever there is new knowledge creation in any other related technological field. An innovative start-up firm that enters with technology characterized by a higher knowledge centrality in the local knowledge base will thus receive higher knowledge spillovers which will in turn facilitate the firm introduce more innovations. So I propose that:

Hypothesis 2 (H2): An innovative start-up firm will produce more technological innovations if its entry technology is characterized by a higher level of knowledge centrality in the local *knowledge base.*

Characteristics of Local Knowledge Base and Technological Diversification

Firms are likely to span over more than one technology in their innovation activities. Breschi et al. (2003) have studied the extent and the nature of the range of firms' innovative activities and find that the knowledge-relatedness is the key factor affecting firms' technological diversification. Though they do not test the causal relationship directly, it is important to notice the fact that firms diversify technologically along certain directions, which depends on the links and the distance between technological fields. Inspired by their insightful findings, I explore in this study the determinants of innovative start-ups' technological diversification and define it as whether or not an innovative start-up firm taps into new technology fields over the observation period after its entry.

Innovation is regarded as a problem-solving process in which firms access, recombine, and manipulate knowledge to create new one (Katila and Ahuja, 2002). This process is often path-dependent and builds upon existing knowledge and routines that underpin the firm's innovation activities (Nelson and Winter, 1982). The past exploitation in a given domain makes future exploitation in the same domain even more efficient (Levinthal and March, 1993). This in turn leads to the improvement of organizational performance such as decrease of production cost (Asher, 1956), product or service quality enhancement (Argote, 1993) and organizational survival (Baum and Ingram, 1998) due to the learning effects. Although many virtues have been highlighted, organizational learning processes are also subject to some limitations such as the competence trap which drives firms to search new knowledge locally (Ahuja and Lampert, 2001; Katila and Ahuja, 2002; Rosenkopf and Nerkar, 2001) and reduces their explorative deviations from existing activities (Levinthal and March, 1993).

As firm's technological development strategy is influenced by its current environment which provides information about a distinctive opportunity to invest or strategies which will ultimately be associated with competitive advantage (Cockburn, Henderson and Stern, 2000). Innovative start-ups that enter with technologies characterized by high levels of knowledge stock in the local knowledge base experience intense knowledge spillover from the same technology fields and this process reinforces the accumulation of familiar knowledge which in turn facilitates firms introduce more innovations in the same technology fields. So I propose that:

Hypothesis 3 (H3): An innovative start-up firm is less likely to diversify into other technological fields if its entry technology is characterized by a higher level of knowledge stock in the local knowledge base.

There are innovative start-ups enter with technologies that can be used in many other applied areas, meaning that these technologies extensively relate with other technologies in the local knowledge base. Through this well connected knowledge network, there is a circulation and transfer of related technological knowledge (Ramani and Looze, 2002). This means that whenever there is a creation of new knowledge in the related fields there will also be a big potential of knowledge spillovers to firm's entry field. This will make the firm more open to other external technology knowledge and increase the possibility to broaden its scope of search (Argyres and Silverman, 2004; Rosenkopf and Nerkar, 2001). By responding to the potential technology opportunities, firms integrate received external knowledge with their own internal knowledge, which serves as a path-breaking mechanism and enhance the probability to explore various new technological areas eventually. So I propose that:

Hypothesis 4 (H4): An innovative start-up firm is more likely to diversify into other technological fields if its entry technology is characterized by a higher level of knowledge centrality in the local knowledge base.

There are some innovative start-ups that enter with technologies that have high levels of knowledge stock and also extensively relate with other technology fields in the local knowledge base. In this case, these firms do not only receive intensive knowledge spillovers from their entry fields, but also experience high levels of knowledge spillovers from other different but related technological fields. By doing so, firms could acquire adequate technological knowledge and develop sufficient technological capabilities in their core technological fields to the extent that these capabilities help the firms understand better and facilitate them to leverage different kinds of knowledge they receive from other technological fields. This process will eventually lead firms to explore various technological areas that are different from their entry ones. So I propose that:

Hypothesis 5 (H5): The positive (negative) effect of knowledge centrality (stock) on an innovative start-up firm's probability of technological diversification is increasing with the level of knowledge stock (centrality).

METHODS

Research Setting

I investigate the research questions in the context of Information Communication Technology (ICT) industry in China during the period between 1985 and 2009. ICT industry is chosen as a representative example of high-technology industries as the local knowledge plays an important role in firm's innovative activities in this industrial cluster. Theoretical and empirical studies in advanced economies underline the significance of local knowledge spillovers for innovation. However, not much is known about whether local knowledge spillovers work similarly in emerging economies (Kesidou and Szirmai, 2008), such as China. By and large, firms from these economies have been regarded as lack of sufficient capability to capture the local knowledge spillover although these countries have experienced rapid economic development over the last two decades and showed great potential to grow further and catch up even take over the developed countries. It is interesting and also important to understand how firms from emerging economies benefit from local knowledge spillover and compare their growth patterns with the received ones from the advanced economies.

China's ICT industry has experienced rapid growth sine 1990s. It is becoming the most dynamic sector in China's economy and attracting increasing attention from both the academic and business world (Meng and Li, 2002; Wang and Lin, 2008). ICT industry in China is geographically uneven at the national level. I choose one of the biggest ICT clusters in China, Shanghai cluster for this study as it is the representative one in the eastern coastal area where five out of six ICT clusters in China are located.

Data and Sample

It is a common method to use patent data to investigate firm's and regional innovation and technological change (Co, 2002; Hicks, Breitzman, Olivastro and Hamilton, 2001; Johnson and Brown, 2004).The data used in this study is China patent applications and they are obtained from the State Intellectual Property Office (SIPO). SIPO is the governing body and directly affiliated to the State Council with main responsibilities such as organizing and coordinating IPR protection nationwide, standardizing the basic orders of patent administration, drawing up the policies of foreign-related IP work etc. This database covers 4,084,530 patents (include 1,610,798 invention, 1,373,542 utility model and 1,100,190 design) received by SIPO from 1985 (SIPO's first year of activity) to 2009 by firms, institutions and individuals of all countries seeking legal protection for their innovations. SIPO discloses the following information regarding each patent: application number, publication number, application date, publication date, priority information, international classification, applicant(s) name, applicants address, inventor(s) name, patent agency code, patent agent and abstract of the patent. Firm-level data (e.g. founding time, firm size, address/ region where the firm is located, domestic/ foreign firm, etc.) is obtained from Local Administration Office of Industry and Commerce and firm homepage from Internet.

I start with 85,394 patents in Shanghai from 1985 to 2009 together with 60 technology classes (International Patent Classification, 8th edition, 2000) of ICT industry which belong to 4 sub-sectors (Telecommunications, Consumer electronics, Computers, office machinery and Other ICT) to identify 32,783 patents of ICT industry based on IPC codes and use this data to construct the knowledge base. Based on the main IPC codes I identify 14,826 patents applied for by firms excluding the universities, research institutions and individuals to evaluate firm's innovation performance. There are 2,263 unique firms identified that patented at least once in ICT industry from 1985 to 2009. I compare the founding year of these firms with the application year of their first patent. Of the 2,263 firms, I select the firms that satisfy the following criteria.

First, the difference between the application year of firm's first patent and firm's founding year is 5 years or less. Taking 5 as the threshold value as I follow the same logic of Breschi, Malerba and Mancusi (2010) on the innovative start-ups which assumed that truly innovative new entrants are more likely to have applied for their first patent shortly after their foundation and restricted the sample to firms established not earlier than 5 years before their first patent application. Second, application year of the first patent is earlier than 2005. This is because the dependent variable (technological innovation) is measured over a time interval of 5 years. Firms applied their first patent after 2005 can't offer the complete observations for the performance measure therefore they are dropped out from the sample. To test the technological diversification model, I add in the third condition to the criteria: a firm applies for more patents apart from the first patent application after its foundation. In this sample I include only the start-ups that are active in their innovation activities because to be innovative firms in the hi-tech industry firms are supposed to be persistent in the innovation activity. In order to study the development of firm's technology trajectory, a certain level of innovation persistence is required.

Finally a sample of 207 innovative start-ups are identified for technological innovation model and 139 innovative start-ups are drawn for technological diversification model out of a population of 2,263 firms that have applied at least for a patent between 1985 and 2009. Additional firm-level data are collected accordingly.

Variables and Measures

Dependent variable. In the current study, I look at start-up firm's innovation performance, which includes two aspects. One is ***technological innovation*** that is captured by the number of innovations introduced by an innovative start-up firm and it is measured by the total number of patents applied by the firm that is active in the industry and located in the cluster in the subsequent five years after its first patent application. The other aspect of the innovation performance is the ***technological diversification*** of innovation activities. It is defined as whether or not an innovative start-up firm taps into a range of technology fields that are different from its entry field after entry. It is measured by a dummy variable, with 1 indicating the firm has at least one patent application in a technology field that is different from its entry field within the subsequent five years after its first patent application and 0 indicating otherwise.

Independent variables. I examine the characteristic of the technological knowledge in the local knowledge base from two aspects: knowledge stock and knowledge centrality. This concept was proposed by Ramani and Looze (2002). They define an agent (i.e. an individual, an institution, a region or a nation.) as a knowledge producer. The ***knowledge base*** of an agent is defined as a collection of the technological knowledge that an agent possesses and the connections among these knowledge fields. The knowledge base of a geographic location can be characterized by two attributes: one is ***knowledge stock*** that reflects the total amount or strength of a certain type of technological knowledge. The other attribute is ***knowledge centrality*** that indicates the relatedness the focal technological knowledge with other knowledge fields. In this study the knowledge refers to the technological knowledge. I use the terms technological knowledge, knowledge and technology interchangeably.

The total number of patent (invention) applications of ICT industry in Shanghai from 1985 to 2009 is 81,263. Every patent is attributed to one main and several, if any, supplementary technology classes by the national patent office according to International Patent Classification (IPC), which is an internationally agreed, non-overlapping and comprehensive patent classification system. Technology affiliation to one or more technological fields is assigned by SIPO to each patent in the current case and it will be indexed by j or k = 1, 2… m. There exists a vector with m components. A component takes value 1 if the patent is affiliated to the corresponding technology and 0 otherwise. In this study, the knowledge base of Shanghai ICT cluster can thus be represented by the following matrix $\mathbf{M}_i$:

$\mathrm{M_i} = \begin{bmatrix} f_1^i & c_{12}^i & \cdots & c_{1m}^i \\ c_{21}^i & f_2^i & \cdots & c_{2m}^i \\ \vdots & \vdots & \ddots & \vdots \\ c_{m1}^i & c_{m2}^i & \cdots & f_m^i \end{bmatrix}$, in which, the technology vector of technology **k** in the knowledge base of region i (Shanghai ICT cluster in the current case) is: $\mathbf{cv}_k^i = (c_{k1}^i, c_{k2}^i, \dots, f_k^i \dots, c_{km}^i)$, $k \in [1, m]$ and c_{kl}^i is the number of patents that are affiliated both to technology k and l in region i from 1985 until a certain year t. Year t is one year before an innovative start-up firm applies for its first patent in a technology field. It is lagged one year so that I could take into count the time lag between the patent application and patent publication, which is a point in time when the patent is revealed to and accessed by the public. IPC codes in ICT industry can be split into four fields according to the International Patent Classification (8^{th} edition, 2000): telecommunications, consumer electronics, computers, office machinery and other ICT. There are maximum 60 technology fields in an ICT industry cluster and m takes maximum value 60 therefore. ***Knowledge stock*** is defined as the strength or magnitude of the knowledge. The stock of technology k of region i in year t is measured by the number of patent applications that are affiliated to technology k in region i until year t. From the matrix, knowledge stock of technology k in the knowledge base of region i therefore is f_k^i and it equals to the number of patents that are affiliated to technology k in region i. ***Knowledge centrality*** indicates the relatedness the focal technology with other technology fields. The centrality of technology k of region i in year t is measured by the number of technology classes with which the focal technology is connecting or co-classified in the patents within region i until year t. We see from the matrix that knowledge centrality of technology k in the knowledge base of region i therefore is the number of non-zero components of technology vector $\mathbf{cv_k^i} = (c_{k1}^i, c_{k2}^i, \dots, f_k^i \dots, c_{km}^i)$, other than f_k^i.

Control variables. There are firm specific and industry-related factors will affect the innovation performance of the firms. I include the following variables as controls in the model. ***Size of the firm*** has been argued to affect the firm's innovation propensity. Larger firms may have higher level of innovation activities due to the larger recourse base in terms of financial capital, human capital and organizational routines to explore new technologies. On the other hand, smaller firms have less rigid organizational structure and more flexibility adjusting their resources to conduct innovation activities. Size is introduced as control through measuring the number of employees of the firm at founding time and it is classified into small firm (0-100 employees), medium and large firm (more than 100 employees). I set dummy variable with the medium and large firms as the reference group. It has been argued that older firms develop more innovations due to the accumulation of experiences and capabilities over longer period of time of survival but this can also be detrimental due to organizational inertia that prevents firms from reacting to the changing environment actively. I control the ***age at entry*** of the firm as of the difference between the founding year and application year of its first patent. ***Ownership of the firm*** captures that whether a firm is invested by domestic capital, and foreign capital or both (foreign-involved). Foreign ownership is often associated with direct technology transfer from multinational companies to local affiliates, larger fraction of skilled workers and higher efficiency, thus one can expect a positive relationship between foreign ownership and innovation output. Here ownership of the firms is classified into domestic firms, foreign-involved firms. I set dummy variable with the foreign-involved firms as the reference group. ***Type of the firm*** refers to the affiliation of a firm. Firms can be classified into subsidiary firms and independent firm. I set dummy variable with the independent firms as the reference group. From the technological perspective, there are four ***sub-sectors of ICT industry*** according to IPC codes: Telecommunications, Consumer electronics Computers, office machinery and other ICT. I set dummy variables to each sub-sector in order to capture the differential technological opportunities among these sub-sectors. ***Foreign patent*** refers to whether or not a firm has applied for a patent in United States Patent and Trademark Office (USPTO), European Patent Office (EPO) or both within 5 years after foundation. If yes, code dummy=1, otherwise, dummy=0. Applying patents from one of the three major jurisdictions: Japan Patent office (JPO), USPTO or EPO reflects firm's innovation capability in technological frontier due to the higher perceived importance and quality of the patents in these patent authorities (Henderson and Cockburn, 1994). ***Team size*** is the size of the inventors' team and it is measured by the number of inventors of the first patent applied by the firm after foundation. Being listed as an inventor of a patent, a person must make original and innovative contribution to the invention. This variable thus captures the initial level of the knowledge-based human resources in an innovative start-up firm which are generally small in size and lack of human and financial recourses in initial stage. Having a larger inventors' team size indicates a firm having invested more on human capital and possessing a broader knowledge, therefore the more innovations the firm will develop. ***Co-paten*** refers to whether or not firm's first applied patent is collaborated with other applicants. I control the collaboration of the firms with other institutions (firms, universities and research institutions) as collaboration facilitates innovation through offering the firm some combination of risk sharing, obtaining access to new technologies, pooling complementary skills and speeding innovation processes (Powell, Koput and Smith-Doerr, 1996). I set dummy variables with the solo applicant as the reference group. ***Inventor experience*** refers to whether or not any inventor in the first patent of the firm has invented and applied for at least one patent before. I set dummy variables with the non-experienced inventors as the reference group. Firm's performance is likely to be affected by the competitive environment in which firm operate. Higher level of concentration implies lower level of competition, and vice versa. Innovation declines with competition, as more competition can reduce innovation incentives by lowering post-innovation profits (Gilbert, 2007). However, competition can also promote innovation by reducing the cost of failing to invest in research and development and giving firms greater incentives to pre-emptively innovate (Blundell, Griffith and Van Reenen, 1999). The ***level of concentration*** in each technological field in a certain year is controlled and measured by the Herfindahl index for patent applications in each technological field of ICT industry by the firms within the cluster.

Econometric Models

Technological innovation is measured by the number of patents applied for by a firm. The simplest form of a count data model is the one where the dependent variable follows a Poisson distribution, so its variance is set equal to the mean (Baptista and Swann, 1998). Since the dependent variable in the current is count data with over dispersion (variance is larger than the mean), I adopt negative binomial regression model with robust option, which is more appropriate for this analysis (Hausman and McFadden, 1984). The robust standard errors attempt to adjust for heterogeneity in the models. The other dependent variable is technological diversification and it is measured by a dummy variable which indicates whether or not a firm has at least one patent in other technological fields that is different from its entry field over the subsequent five years after its first patent application. I adopt probit regression model with robust option.

RESULTS

Descriptive statistics and correlations of the variables in the technological innovation model are presented in Table 1 and the corresponding values for technological diversification model are presented in Table 2. Table 1 shows that knowledge centrality has positive relationship with all the three alternative measures of firm's technological innovation. Knowledge stock has a positive relationship only with core technological innovation but very weak positive relationships with firm's total and related technological innovation. Table 2 shows knowledge stock, as expected, is negatively associated with technological diversification. While knowledge centrality and the interaction term between knowledge stock and centrality shows unexpected negative correlation with technological diversification. Among various control variables, firm size, foreign patent and team size show consistent correlations with three measures of firm's technological innovation. The level of concentration in the technological field is negatively associated with firm's total and core technological innovations. It also correlates with knowledge stock and centrality in both technological innovation and diversification models. Firm age, ownership and type reasonably correlate with firm size.

Insert Table 1 and Table 2 about here

Knowledge Base and Technological Innovation

The results of estimating technological innovation model are reported in Table 3. Apart from knowing a firm's overall innovation performance I also introduce other finer measures such as ***core technological innovation*** (firm's innovation performance in its entry technology field) and ***related technological innovation*** (firm's innovation performance in all technology fields but its entry field) in order to capture how many of the innovations are from firm's entry technology field (i.e. core innovation) and how many are from other technology fields but related to the main field (i.e. related innovation) respectively. Based on the IPC codes of each patent, core innovation is measured by the number of patent applications with the main IPC code belongs to firms' entry technology. Related innovation is measured by the number of patent applications with one of the secondary IPC codes belongs to firm's entry technology.

I thus introduce three models to test Hypothesis 1 and Hypothesis 2. The only difference among these three models is the measure of the dependent variable. Total technological innovation (Model 1), core technological innovation (Model 2) and related technological innovation (Model 3) are adopted respectively in the models. All the three models are significant at 0.01 level. The alpha values (alpha equals to 0) for negative binomial regression models are also significant at 0.01 level, which indicates the negative binomial regression model fits better than a Poisson regression model.

Table 3 displays the estimates of the impact of knowledge stock and centrality on firm's technological innovation controlling for the characteristics of firm and industry. I use STATA command mfx to compute the correct marginal effect of each variable while holding other variables at their mean. The marginal effects of the variables are reported in Table 3.

Insert Table 3 about here

Hypothesis 1 predicts that an innovative start-up will produce more technological innovations if it entry technology is characterized by a higher level of knowledge stock in the local knowledge base. Model 1 shows that knowledge stock has no effect (the coefficient is negative and not significant) on firm's total technological innovation. After introducing the finer measures of technological innovation, the core and related technological innovation, I test the alternate measures in Model 2 and Model 3 respectively. Model 2 shows that knowledge stock has a positive and significant effect on firm's core technological innovation. The magnitude of the effect is 0.0002. The economic meaning of the result can be understood as, other things being equal, if the number of patent applications in a certain technological field within an industrial cluster increased by one patent application, an innovative start-up entering with the same technology in the cluster would have 0.0002 more patent application in its entry field during the subsequent five years after its entry. Model 3 shows that knowledge stock has no effect (the coefficient is negative and not significant) on the related technological innovation. The received results offer partial support for H1.

Hypothesis 2 proposes that an innovative start-up will produce more technological innovations if it entry technology is characterized by a higher level of knowledge centrality in the local knowledge base. Table 3 shows that knowledge centrality has significant and positive effects on both total and core technological innovation. The magnitude of the effect is 0.17 and 0.02 respectively. The economic meanings of the results can be understood as followings. Other things being equal, if the number of technological fields which are related to a focal technology within an industrial cluster is increased by one, the number of patent applications in all ICT technological fields of an innovative start-up entering the focal technology field would increase by 0.17 and by 0.02 in its entry technological field (i.e. the focal technological field) during the subsequent five years after its entry. H2 is therefore supported by the results.

Knowledge Base and Technological Diversification

Table 4 presents probit regression results for a dummy codification of technological diversification. Model 4 is the baseline model including only control variables. Model 5 displays the estimates of the impact of knowledge stock (H3), knowledge centrality (H4) and the interaction between knowledge stock and centrality (H5) on firm's technological diversification controlling for the characteristics of firm and industry discussed above. All the models are significant at 0.01 level indicating a good fit of the selected models.

Insert Table 4 about here

Hypothesis 3 contends that an innovative start-up is less likely to diversify into other technological fields if its entry technology is characterized by a higher level of knowledge stock in the local knowledge base. However, the coefficient of knowledge stock in Model 5 shows insignificant effect on firm's technological diversification. Hypothesis 4 proposes that an innovative start-up is more likely to diversify into other technological fields if its entry technology is characterized by a higher level of knowledge centrality in the local knowledge base. The regression result in Model 5 shows the opposite, the coefficient of knowledge centrality is negative and significant. Hypothesis 5 predicts that an innovative start-up is more likely to diversify into other technological fields if its entry technology is characterized by both higher knowledge stock and centrality in the local knowledge base. The coefficient of the interaction term in Model 5 shows significant positive sign as predicted.

It is important to note that the interpretations of the coefficients here, thus the effect of each variable, are not straightforward. Because in a nonlinear regression model, the interaction effect and the effects of each interacted variables depend on other independent and control variables. They are not equal to the corresponding coefficients in the regression model, they may have different signs for different values of the variables. The statistical significance can't be tested with a simple t test but have to be calculated (Ai and Norton, 2003; Hoetker, 2007; Norton, Wang and Ai, 2004). I use STATA command 'predicnl' and 'inteff' (Norton et al., 2004) to compute the correct marginal effects of the two interacted variables, their interaction effects, z-statistics and graph the effects for each observations of the probit model.

After running predicnl command, we can see from Table 5 that the mean effect of knowledge stock is negative (-0.00001). This is the average of the effects of knowledge stock calculated for each observation. It means, on average, for one unit increase in knowledge stock of a particular technology in the local knowledge base, the probability of diversification of innovative start-ups entering with the same technology will decrease by 0.001%. The average of effects is different from the effect of average observation that is obtained via the common approach by setting the other variables at their mean (Hoetker, 2007). Train (1986) argues that the average of effects is more informative because it is unlikely that any single observation actually has the mean value of all variables. The effect of knowledge stock varies widely. Given a predicted probability of technological diversification, for some observations, the effects are positive, and for others, the effects are negative (see Figure 1). The effects are mainly centered on 0 and get dispersed where the innovative start-ups have a predicted probability of technological diversification around 0.6. The effects of knowledge stock are statistically significant for the firms that have a predicted probability of technological diversification from 0.4 to 0.6 at 0.05 level. For the rest of the observations, the effects are not significant.

Insert Table 5 and Figure 1 about here

Table 6 shows that the mean effect of knowledge centrality is negative (-0.012). It means on average, for one unit increase in knowledge centrality of a particular technology in the local knowledge base, the probability of technological diversification of innovative start-ups entering with the same technology will decrease by 1.2%. For most of the observations, the effects of knowledge centrality are negative. There are only a few observations show positive effects (see Figure 2). Overall, the magnitude of the effects has a U-shaped trend across all the observations. It decreases with the predicted probability of technological diversification and reaches its minimum value (-0.05) for the innovative start-ups that the predicted probability of technological diversification is around 0.5, after which the magnitude of the effect starts to increase. In terms of the statistical significance of the effects, for the group of innovative startups whose predicted probability of technological diversification is about from 0.4 to 0.6, the effects of knowledge centrality are mostly significant at 0.05 level. For the other firms that predicted probability of technological diversification is below 0.4 and above 0.6, the effects of knowledge centrality are statistically insignificant at 0.05 level.

Insert Table 6 and Figure 2 about here

After running the inteff command, we can see from Table 7 that the mean interaction effect is positive (0.00003). It means on average, for one unit increase in both knowledge stock and knowledge centrality of a particular technology in the local knowledge base at the same time, the probability of diversification of innovative start-ups entering with the same technology will increase by 0.003%. For most of the observations, the interaction effects are positive, and for a very few observations that have a predicted probability of technological diversification over 0.9, the interaction effects are negative (see Figure 3). The magnitude of the interaction effect has an inverted U-shaped trend across all the observations. It increases with the predicted probability of technological diversification and reaches its maximum value (0.0008) for innovative start-ups having predicted probability of technological diversification around 0.4, after which the magnitude of the interaction effect starts to decrease. In terms of the statistical significance of the interaction effects, for innovative startups whose predicted probability of diversification is about from 0.4 to 0.6, the interaction effects are mostly significant at 0.05 level. On the other hand, for the firms that predicted probability is below 0.4 and above 0.6, only a few have statistically significant interaction effects at 0.05 level.

Insert Table 7 and Figure 3 about here

DISCUSSION

Knowledge Base and Technological Innovation

Overall, from the results of the technological innovation model I find that higher levels of knowledge stock in an innovative start-up's entry technological field within the local knowledge base contribute only to the number of innovations that the firm produces in its entry filed (core technological innovation) and has little contribution to the technological innovation in the related technological fields (related technological innovation) and the overall technological innovation (total technological innovation) when holding other influencing factors constant.

A possible explanation for the results is two-fold. First, innovation is path-dependent and builds upon existing knowledge and routines of the firm. The past exploitation in a given domain makes future exploitation in the same domain even more efficient (Levinthal and March, 1993; Nelson and Winter, 1982). Higher knowledge stock of firm's entry technology in the cluster increases the localized knowledge spillover that enhances the propensity and potentiality of the firm's innovation activities in its entry field. Meanwhile, higher levels of knowledge stock in a certain technological field may also setup an invisible boundary for these firms while they are looking for new solutions to the problems. This will lead firms to search locally within their entry fields and reduce the innovations in other technological fields. Because the number of total technological innovation equals to the sum of the core and related technological innovation, we observe knowledge stock only has weaker, though insignificant effect on firm's total technological innovation than its effect on the core technological innovation.

Results also show that knowledge centrality has no significant influences on firm's technological innovations in the related fields. This is probably due to the measure of knowledge centrality which only reflects the level of connections of the focal technology with other technological fields but does not take into consideration the intensity of the knowledge spillover through these connections. The knowledge flow between related technological fields could vary so greatly that alters the magnitude of the effect that is driven by the different connections among firm's entry technology and other related technological fields.

Knowledge Base and Technological Diversification

Overall, the results obtained from the technological diversification model show that knowledge stock alone has predicted negative effect on innovative start-ups' technological diversification. Contrary to the prediction, knowledge centrality alone has significant negative effect on innovative start-ups' technological diversification. The interaction between knowledge stock and centrality has the predicted sign that indicates a positive effect. As to the statistical significance, however, all the three effects are only significant over the observations where innovative start-ups have a predicted probability of technological diversification from 0.4 to 06.

One way to interpret the pattern of the results is to argue that due to the S-shaped response curve in probit analysis, a given change in the probability is more difficult to obtain when the probability is closer to the limits of 0 and 1, and it is easier to obtain when the indeterminacy is highest, where the probability is around 0.5 (Cox and Snell, 1989; Hanushek and Jackson, 1977; Huang and Shields, 2000). We observe knowledge stock, knowledge centrality and their interaction has significant effects over the observations where innovative start-ups have a predicted probability of technological diversification from 0.4 to 06. These firms are roughly ambivalent between diversifying into other technological fields and staying in their entry fields. They are more likely to be influenced by the environmental conditions such as knowledge spillover from the outside of the firms than those firms that are more determinant to or not to diversify, thus have either much higher or lower probability to diversify. This is because the diversification decision of the latter will be more easily to achieve mainly through evaluating the firm-level resources and capabilities, while for the former, internal evaluations simply do not provide sufficient confidence to take the decision and the influences coming from their external environment become more pronounced under this situation.

The negative effect of knowledge centrality on innovative start-ups' technological diversification choices is in line with the earlier theoretical argument and empirical result of H2 which shows knowledge centrality is positively associated start-ups' technological innovation in the entry fields but contribute little to other related fields. Moreover, the justification of the result could also be that higher knowledge centrality implies a more fragmented market and dynamic environment. It might be a wise choice for these start-ups to stay specialized and efficient in their entry fields which is more likely to result in successful outcomes in a dynamic environment (Levitt and March,1988) because the specialization based on core competences is difficult to imitate and can provide the basis for a sustainable competitive advantage (Barney,1991).

CONCLUSIONS AND IMPLICATIONS

In this study, I investigated the localized knowledge spillover in an industrial cluster and the implications for start-ups innovation performance through exploring the relationship on the one hand two characteristics of local knowledge base of the industry cluster, knowledge stock and knowledge centrality, and on the other hand innovative start-up's technological innovation and diversification. I argued that agglomeration externality did not benefit innovative start-ups in a cluster equally. Alongside the agglomeration effect, the attributes of firm's entry technology in the local knowledge base played an important role in determining the way of knowledge spillover and firm's innovation performance. Focusing on a setting where intensive knowledge spillover is likely to be observed, one of the biggest ICT clusters in China was selected. I asked first, why firms within a cluster had different levels of technological innovation. Second, why some firms became technologically specialized and others diversified over time though they all started with one or few types of technologies within the same geographic location. Third, how the localized knowledge spillover influenced firm's innovation performance. The results showed that an innovative start-up firm produced more technological innovations if its entry technology was characterized by a higher level of knowledge centrality in the local knowledge base. While the knowledge stock showed only significant effect on firm's core technological innovation that might be due to the coexistence of 'learning' and 'lock-in' effects of the firm's innovation. This study also showed that over time innovative start-ups demonstrated different propensities of technological diversification in their innovation activities. Knowledge stock and centrality of firm's entry technology in the local knowledge base showed negative effect on the probability of technological diversification. The higher the knowledge stock or centrality of a firm's entry technology in the local knowledge base the less likely the firm would diversify into other technological fields. The interaction between knowledge stock and centrality showed positive effects on the probability of firm's technology diversification. Innovative start-ups were more likely to diversify into other technological fields when both the knowledge stock and centrality retains a higher level.

This study contributes to the economic geography and innovation strategy literature by focusing on the performance implication of clustering effect on the innovative start-ups and highlighting the importance of investigating the specificities and the characteristics of the knowledge in the local knowledge base in order to understand the micro-foundations of knowledge spills over and the ways in which knowledge spillover influence firm's innovation performance. This study also provides important practical and managerial implications. To understand the driving forces behind the superior performance of innovative start-ups located in a cluster we have to distinguish what resources have been agglomerated in the cluster, in which way they are agglomerated and which types of firms could benefit most from this agglomeration. The agglomerated resources do not benefit firms in a cluster equally. Innovative start-ups with a certain type of entry technology demonstrate better innovation performance than other firms in the same cluster. Even though entering a high-tech industry cluster, innovative start-ups should carefully choose the entry technologies upon which to build their business through evaluating the characteristics of local knowledge base in order to access, absorb and fully utilize the localized knowledge spillover.

This study has some limitations that suggest a number of directions for future research. First, generalizability of the findings from this study might be questioned in that it investigates only one cluster in one industry. This study can be extended to other hi-tech industries where the localized knowledge spillover and externality play more important role than other types of agglomeration resources. Future research could consider multi-cluster and multi-industry studies.

It is interesting to ask if there are industry-specific and location-specific factors that might be relevant; if there exist a generic pattern of the relationship within an industry across different clusters or across different industries. Second, I focus on the firm-level innovation performance. Due to the interplay between the firm and cluster, the level of analysis can be extended to the cluster or regional level. Future research can carry out studies on the cluster evolution and regional diversification in terms of technological knowledge and economic activities. The characteristics of the technological knowledge in the local knowledge base shape the development opportunities of technologies at the regional level. Third, this study is based on China patent data that currently does not provide the information on patent citations. Patent co-classification provides sufficient information on the connections between various technological knowledge, but not sufficient to trace the real knowledge flow. Thus, I do not directly test the relationship between the knowledge spillover and firm performance. Extending the current study based on the US and European data are recommended for future studies. Forth, the innovation performance measure in this study is based on firm's patent application. There are well-documented limitations associated with the adoption of patent data to measure the innovation output in existing literature. The current study focuses on the performance of the innovative start-up firms. The specialties of this kind of firm (it has to be new and conduct innovations), the average time (12-32 months) it takes from the date of application to that of the grant of a patent in China and even longer lead time to realize the commercialization of the patented invention make the patent application the most appropriate measure for firm's innovation performance since it is close to the first moment when firms make innovative achievements.

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TABLE 1.

Descriptive Statistics and Correlations of Variables (Technological Innovation Model)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Mean	5.31	0.89	4.42	477.54	12.15	0.67	0.33	1.98	0.75	0.25	0.29	0.71	0.13	2.52
Std. Dev.	9.82	2.38	8.74	716.58	6.84	0.47	0.47	1.55	0.43	0.43	0.46	0.46	0.33	1.79
1 Technological innovation (total)	1.00													
2 Technological innovation (core)	0.55	1.00												
3 Technological innovation (related)	0.97	0.35	1.00											
4 Stock	0.04	0.13*	0.01	1.00										
5 Centrality	0.21**	0.19**	0.18**	0.23***	1.00									
6 Size (small)	-0.25***	-0.18**	-0.23**	0.07	-0.06	1.00								
7 Age at entry	0.10	0.11	0.08	0.02	0.23***	-0.18**	1.00							
8 Ownership (domestic)	0.00	0.08	-0.03	0.08	0.05	0.15*	-0.03	1.00						
9 Type (subsidiary)	-0.09	-0.01	-0.10	-0.09	-0.03	-0.19**	0.07	-0.40***	1.00					
10 Foreign patent	0.23***	0.15*	0.22**	0.07	0.10	-0.20**	0.06	-0.12†	-0.11	1.00				
11 Team size	0.21**	0.13†	0.20**	0.122†	0.03	-0.18*	0.14	-0.02	0.05	0.04	1.00			
12 Co-patent	0.01	-0.07	0.03	0.11	0.03	-0.07	0.10	0.10	-0.02	0.00	0.33***	1.00		
13 Inventor experience	0.04	-0.08	0.07	0.08	0.09	0.08	0.09	-0.04	-0.01	-0.03	0.32***	0.27***	1.00	
14 Concentration	-0.12†	-0.17*	-0.08	-0.35**	-0.62**	-0.09	-0.10	-0.10	-0.09	-0.01	-0.09	-0.02	-0.08	1.00

Number of observations: 207
******* p< 0.001,
****** p<0.01,
***** p<0.05,
† p<0.1

TABLE 2.

Descriptive Statistics and Correlations of Variables (Technological Diversification Model)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Mean	0.77	0.00	0.00	958.60	0.60	0.40	2.09	0.74	0.26	0.31	0.70	0.33	0.06	0.34	0.28	0.16	2.67
Std. Dev.	0.42	766.10	6.74	3139.00	0.49	0.49	1.54	0.44	0.44	0.46	0.46	0.47	0.24	0.47	0.45	0.37	1.92
1 Technology diversification	1.00																
2 Stock	0.02	1.00															
3 Centrality	-0.07	0.19*	1.00														
4 Stock x Centrality	-0.01	-0.54***	-0.06	1.00													
5 Size (small)	-0.11**	0.13	-0.12	-0.03	1.00												
6 Age at entry	0.02	0.01	0.23**	0.12	-0.26**	1.00											
7 Ownership (domestic)	0.01	0.05	0.07	0.01	0.13	-0.04	1.00										
8 Type (subsidiary)	0.05	-0.09	-0.02	0.00	-0.11	0.06	-0.40***	1.00									
9 Sector (telecommunication)	-0.01	-0.27**	-0.24**	0.06	-0.10	-0.01	-0.03	-0.01	1.00								
10 Sector (customer electronics)	-0.09	-0.14	-0.12	0.07	0.01	0.03	-0.07	-0.03	-0.18*	1.00							
11 Sector (PC, office machinery)	-0.07	-0.07	0.45***	0.26**	0.02	0.07	0.13	0.02	-0.49**	-0.18	1.00						
12 Foreign patent	0.14	0.08	0.04	-0.09	-0.16†	0.04	-0.03	-0.06	0.01	-0.03	0.00	1.00					
13 Team size	-0.05	0.16†	0.04	-0.12	-0.12	0.13	0.09	-0.15†	0.00	0.04	-0.09	0.02	1.00				
14 Co-patent	-0.03	0.11	-0.02	-0.18*	-0.05	0.07	0.10	-0.08	0.00	0.11	-0.15	0.04	0.36***	1.00			
15 Inventor experience	0.09	0.15†	0.11	-0.15†	0.08	0.06	0.00	0.09	-0.09	0.05	-0.04	-0.03	0.46***	0.33***	1.00		
16 Concentration	0.004	-0.37***	-0.63***	0.35***	-0.04	-0.11	-0.09	0.01	0.38***	0.07	-0.37***	0.00	-0.16*	-0.04	-	1.00	
17 No. of technological innovation	0.31***	0.00	0.24**	-0.09	-0.22*	0.08	0.02	-0.14	-0.05	0.01	0.10	0.22*	0.21*	0.01	0.07	-	1.00

Number of observations: 131

******* $p < 0.001$,

****** $p<0.01$,

***** $p<0.05$,

† $p<0.1$

TABLE 3.

Technological Innovation Models (Negative Binomial Estimation)

	Model 1. Tech. Innovation (total)		Model 2. Tech. innovation (core)		Model 3. Tech. innovation (related)	
	Coefficient	Marginal effect [b]	Coefficient	Marginal effect	Coefficient	Marginal effect
Knowledge Stock	-0.00002	-0.0001	0.0003 †	0.0002†	-0.0001	-0.0004
Knowledge Centrality	0.04 †	0.17†	0.05 †	0.02†	0.04	0.13
Size [a] (small)	-0.56 *	-2.57*	-0.83*	-0.50 *	-0.56 *	-2.19 †
Age at entry	0.09	0.36	0.13	0.06	0.07	-0.25
Ownership [a] (domestic)	-0.05	-0.22	0.53	0.23	-0.18	-0.64
Type [a] (subsidiary)	-0.31	-1.21	-0.08	-0.04	-0.41	-1.31 †
Foreign patent [a]	0.87 **	5.11*	0.71 †	0.48	0.86 **	4.24 *
Team size	0.23 **	0.94 **	0.31 **	0.16 **	0.20 *	0.70*
Co-patent [a]	-0.70 *	-2.259*	-1.60**	-0.48***	-0.50	-1.46 †
Inventor experience [a]	-0.13	-0.55	-0.70 *	-0.34†	-0.01	-0.04
Concentration	0.36	1.49	-0.59	-0.30	0.45	1.56
Intercept	0.61		-1.72 *		0.64	
χ^2	55.94***		49.41***		46.42***	
Log pseudolikelihood	-501.76		-214.96		-459.86	

No. of observation: 207

****** p<0.01,

***** p<0.05,

† p<0.1

(a) Marginal effect is for discrete change of dummy variable from 1 to 0.

(b) Marginal effect is calculated while hold the other variables at their mean.

TABLE 4.
Technological Diversification Model (Probit Estimation)

	Model 4	Model 5
Knowledge stock		0.0001
Knowledge centrality		-0.06 †
Stock x Centrality		0.0002 *
Size (small)	-0.34	-0.44
Age at entry	0.06	0.05
Ownership (domestic)	0.67 †	0.68 †
Type (subsidiary)	0.43	0.40
Sector (telecommunication)	-0.72 †	-0.68
Sector (customer electronics)	-0.61	-0.99 †
Sector (computer office machinery)	-0.97 *	-1.30 *
Foreign patent	-0.48	-0.60
Inventor experience	0.67 *	0.83 *
Team size	-0.21 *	-0.28 **
Co-patent	-0.60	-0.37
Concentration	0.04 †	-1.47
No. of technological innovation	0.32 ***	0.33 ***
Intercept	0.15	0.71
χ^2	29.64**	31.48*
Log pseudolikelihood	-47.21	-44.21
Pseudo R2	0.33	0.37

No. of observation: 131
*** p< 0.001,
** p<0.01,
* p<0.05,
† p<0.1

TABLE 5

Variable	Observations	Mean	Std. Dev.	Min	Max
Effect of knowledge stock	131	-0.00001	0.0002	-0.0006	0.0008
Standard error	131	0.0001	0.000157	0	0.0007
t-statistic	130	-0.23	1.21	-2.33	2.32

FIGURE 1
Effect and Statistical Significance of Knowledge Stock

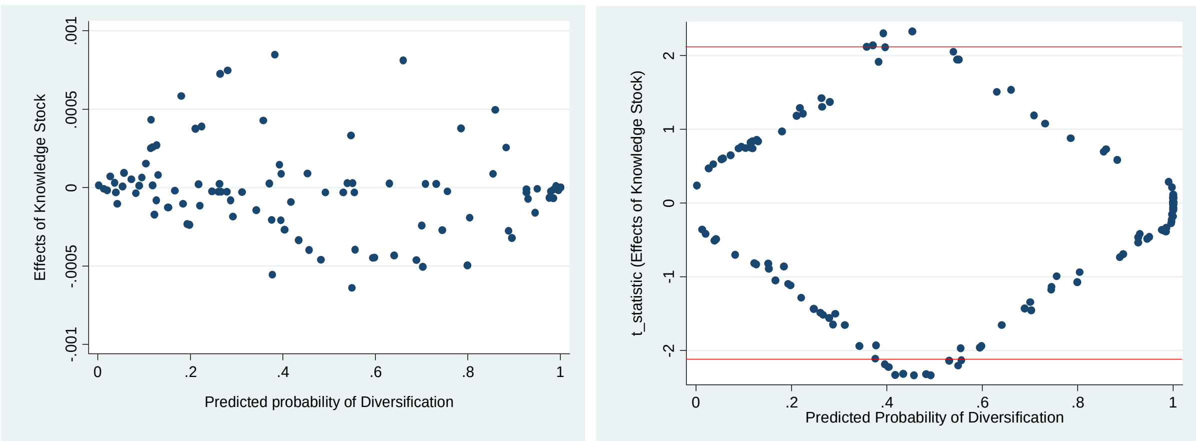

TABLE 6

Variable	Observations	Mean	Std. Dev.	Min	Max
Effect of knowledge centrality	131	-0.01207	0.0306	-0.0535	0.1281
Standard error	131	0.01933	0.0168	0	0.0890
t-statistic	130	-0.74	0.96	-2.59	2.05

FIGURE 2
Effect and Statistical Significance of Knowledge Centrality

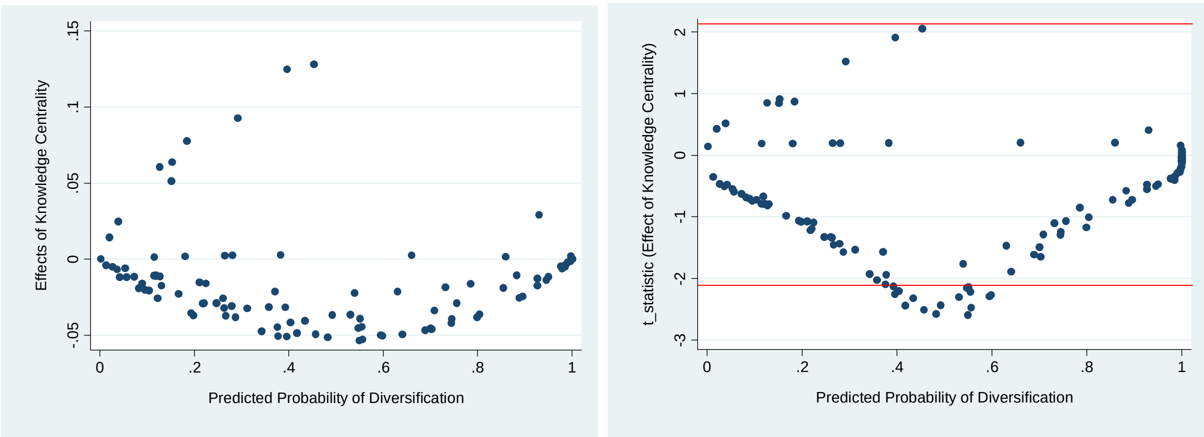

TABLE 7

Variables	Observations	Mean	Std. Dev.	Min	Max
Interaction effect	131	0.00003	0.00003	-0.00002	0.00008
Standard error	131	0.00002	0.00002	0	0.00006
z-statistic	127	0.93	0.93	-1.25	2.60

FIGURE 3
Interaction Effect and Statistical Significance